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An Active Contour for Underwater Target Tracking and Navigation

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Abstract

This paper presents a vision based tracking system for routine underwater pipeline or cable inspection for autonomous underwater vehicles (AUV's). The objective of this research paper is to investigate the issues of pipeline detection, including pose and orientation measurements in underwater environments. The proposed visual tracking system used an active contour method to track underwater object in image sequences. The B-spline based active contour is used to define the underwater pipeline boundaries in image sequence, followed by series of image processing techniques are applied for feature extraction. The active contour deformed based on extracted features. The dynamic curve fitting method is used to measure the pose and orientation of underwater pipeline. To propagate the active contour over image sequence Kalman filtering is used. The Kalman filter updates the state of underwater object. Moreover, it also provides guidance and control to the vehicle when cable or pipeline is fully or partially covered by the sand or marine flora. In order to show the effectiveness of the proposed system, the system is tested on real underwater images. From the experimental results, it is observed that the maximum error is less then 10 pixels which show the robustness of tracking algorithm.

Keywords

Underwater pipeline tracking, active contour, Kalman filtering.

1. Introduction

Traditionally, inspections and maintenances of underwater objects are carried out by using a remotely operated vehicle (ROV) controlled from the mother ship by a trained operator [1]. The effective use of ROV's requires relatively large mother vessel that increase the cost of operations. The tethered cable limits both the operation range and vehicle movements. Moreover, it also required lot of efforts from the operator to concentrate when long mission are carried out. Autonomous underwater vehicles or AUV's do not have such limitations and offer cost effective alternative to the ROV's. They have no tether cables between the mother vessel and vehicle and carry their power supply onboard. AUV's have a wider range of application in both commercial and non commercial industries. Of particular interest in this paper is the implementation of an AUV vision system for routine underwater pipeline inspection and maintenance applications. The usage of underwater pipeline or cables are increased many fold and routine inspection and maintenance are very essential for proper functioning and to protect them from marine traffic [2].

Recently, several approaches to underwater pipeline tracking have purposed utilizing different characteristics such as underwater pipeline or cable models [3] (3D or 2D) and computational methods [4] (template matching, Hough transform, neural network, standard or extended Kalman filter). Conservatively, these approaches are classified into two distinct groups [1]: feature based approach and model based approach. The feature based approach performs tracking by combining the low level features such as boundaries or edges of underwater pipelines or cable [5]. However this technique may fail in case of occlusion due to growth of underwater plants or due to mad or sand on pipeline or cable. On the other hand the model based approach based on prior knowledge or object model such as straight line or structure of the underwater pipeline or cable [3, 6]. It requires few parameters to present underwater object and robust against noise and missing date or partial occlusion. This paper purpose a model based approach to detect and track underwater pipeline in complex marine environments. The objective of this research paper is to design and implement a vision guidance system for autonomous underwater vehicle that can track and inspect the underwater installation. A B-spline based active contour model is used to define the underwater pipeline or cable on image sequences and then series of image processing techniques are used to extract feature of underwater object. After that, shape space transformation is used for contour deformation. The recursive curve fitting is used next to obtain the image measurement. To propagate the contour over an image sequence a dynamic model is used to predict the pose and orientation measurement. The Kalman filter is then used to find the optimal estimation by fusing the both image measurement and the predict state of underwater object.

The rest of paper is organized as follows: section 2 will presents the various image processing techniques that used for object detection in marine environments. Section 3 will discusses the method for underwater pipeline modeling and visual measurement method. Section 4 will explain the tracking algorithm on static images and section 5 will present the dynamic modeling technique and Kalman filtering method for underwater pipeline tracking. Section 6 will discuss the results obtained by testing the purposed system on real underwater images and finally section 7 will end the paper with conclusion and future works.

2. Image Processing

At first the images acquired by the AUV onboard video camera are converted into the gray scale. There are several methods to convert an RGB images into the grayscale [1], however these are not suitable for autonomous application. To convert RGB image into the grayscale different RGB channels are analyzed separately to enhance the image and extract boundary information of object in underwater environment as shown in figure 1. After doing series of experiments on real underwater images it is observed that the red channel shown very good results compare to green and blue channels. On the basis of these analyses only red channel is used for further processing.

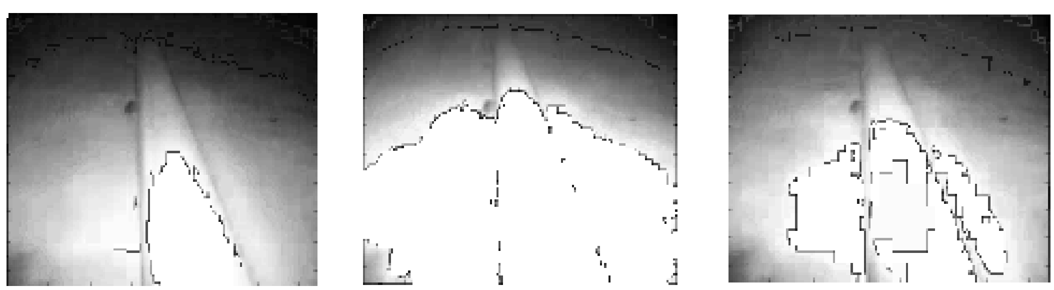
The next phase of image processing is the detection of pipeline boundary. Before detection of object boundary, edge detection is performed to convert gray scale image into the binary image. To avoid the computational burden, Sobel edge detection is used.

Once image is converted into the binary, parameterized Hough transform is used to detect pipeline contour. The parametric equation of Hough transform is given below:

$$\rho = x\cos\theta + y\sin\theta \qquad (1)$$

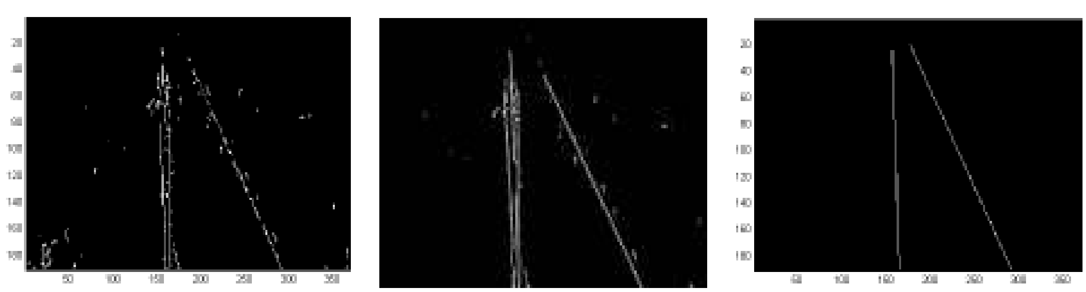
At first all edge points are transformed into the Hough space using the equation 1. In order to avoid the computational burden and excessive memory usage of Hough transform, 1000 edge pixels are processed at a time. After transforming all the pixels in Hough space, peak detection is performed and the locations that contain the peaks are recorded. To avoid the quantization problem in Hough transform all the immediate neighborhood of the maximum found suppressed to zero. Once sets of candidate peaks are identified in the accumulator, start and end points of line segmentation associated with those peaks are identified next. If two line segments associated with the each other but separated by less then predefined gap threshold, are merge into a single line. Furthermore the lines that have both Hough parameters within the predefined threshold also merge in order to avoid multiple lines on same location. The start and the end points of line segments represent the outline of the underwater pipeline.

Due to noise and various underwater conditions, object boundaries are detected in segments. To draw a full boundary of the pipeline over an image a slight different



(a) (b) (c)

Figure 1- Result of converting color image into gray image by extracting only the (a) Red, (b) Green and (c) Blue channel.



(a) (b) (c)

Figure 2 - Results of a) Edge image, b) Line segments detection using Hough Transform and c) Final image using Bresenham line Algorithm

approach is adopted. The first and last points of the line segment have been used to calculate the full boundary of the object using line equation. Once the slope of the line is computed from the line equation a Bresenham line algorithm, which is one of the oldest algorithms in computer graphics is used to construct a noise free boundary of the object. Bresenham line algorithm have few advantages, first it is relatively faster and simple to implement and it is robust if part of the pipeline is not visible or occluded. Figure 2 shows the result of Hough transform and Bresenham line algorithm on underwater image.

3. Pipeline Model and Feature Extraction

Once the underwater pipeline is detected using the variety of image processing technique, the next phase is the design of deformable template that represents the underwater pipeline boundaries. The deformable templates use a prior shape model that can be seen as a regularization term in the fitting process. In order to model the underwater pipeline B-spline function is used. B-spline is a piecewise polynomial function that provides local approximation of contour using a small number of parameters refer to as control points. In this project a second order non-uniform B-spline function with six control points is used. The interval of the B-spline function is [0 2] on 2 spans (span 0 and span1). The first three control points use to define the left boundary while, the last three control points are use to define the right boundary of the pipeline. The boundary contour *c(s) = (x(s), y(s))* is then represented using a B-spline function is given below:

$$x(s) = \sum_{i=0}^{5} \mathbf{B}_i(s)\mathbf{Q}_x \qquad 0 \le s \le 2 \qquad (2)$$

$$\mathbf{Q}_x = \left[q_{-1}^x \;\; q_0^x \;\; q_1^x \;\; q_2^x \;\; q_3^x \;\; q_4^x\right]^T,$$

$$\mathbf{B}(s) = (B_0(s), \ldots, B_5(s))$$

and similarly for *y(s)*. The contour *c(s)* of the pipeline boundary is also represented by a vector **Q** with the B-spline basis *U(s)*, so that:

$$c(s) = \left(x(s), y(s)\right) = U(s)\mathbf{Q} \qquad (3)$$

where

$$U(s) = I_2 \otimes \mathbf{B}(s) \text{ and } \mathbf{Q} = \left(\mathbf{Q}^x \quad \mathbf{Q}^y\right) \qquad (4)$$

The I_2 denotes the 2x2 matrix, $\otimes$ is the Kronecker product and **Q** is the x-y coordinate of the B-spline curve.

After modeling the underwater pipeline using the B-spline function, the next step is the visual measurement. Given an image containing the target, the visual measurement process consists of casting normals (also called measurement line) at pre-specified points around the initial or estimated contour. To extract the feature curve in the image, one dimensional feature detector is applied along each measurement line. The feature detector is simply a scanner that scans for intensity variation on the binary image obtained after Hough transform and Bresenham line algorithm. The measurement lines are unit normal vectors and the slopes of the normals are computed by differentiating the B-spline function given in equation 2. Finally figure 3 illustrates the all these concepts.

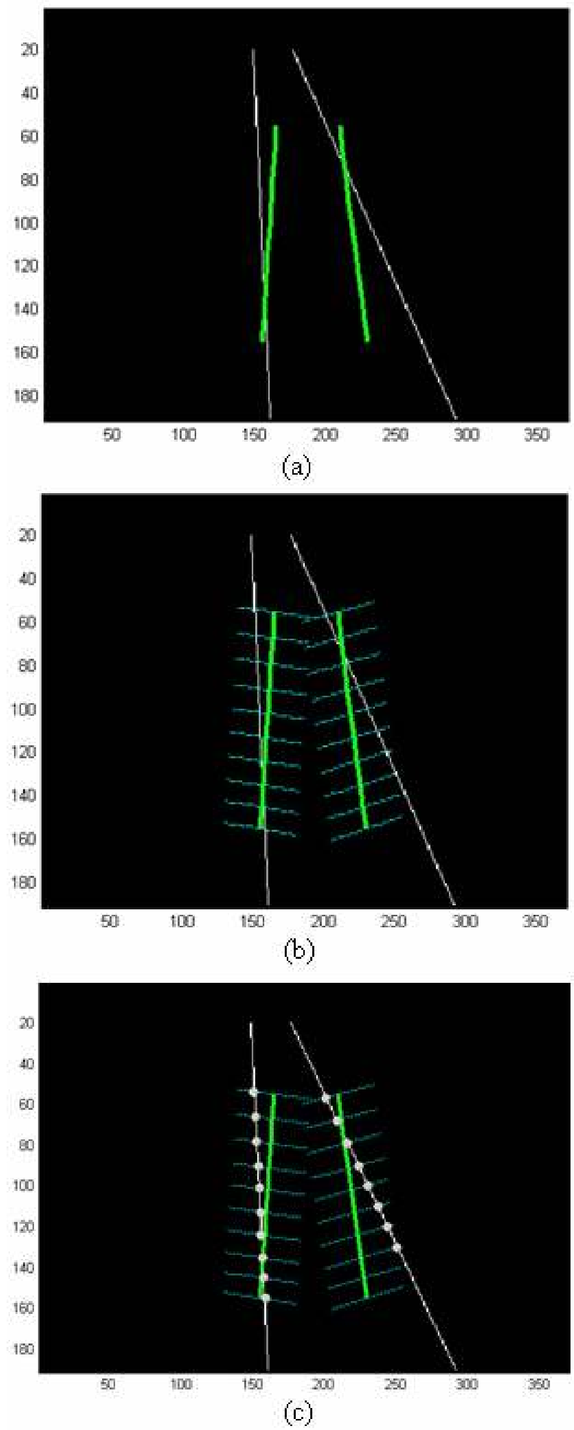


Figure 3 - a) B-Spline Contour That Represents Left and Right Boundaries of Underwater Pipeline, Posted on Underwater Pipeline Image. B) Measurement Line on B-Spline Curve for Feature Extraction. C) Dots Show the Extracted Features using the one-Dimensional Feature Detector.

4. Underwater Pipeline Algorithm

The B-spline model used in this project has six control points. These six control points give 12 degree of freedom. It allows the arbitrary deformation of the contour, which does not happen for any real object and it is desirable to restrict the displacement of this control points to a lower dimensional space. This can be done by using the concept of shape space [7]. The shape space is a linear mapping of a shape vector **X** to a spline vector **Q**, as shown in Equation 5.

$$\mathbf{Q} = W\mathbf{X} + \mathbf{Q}_0 \tag{5}$$

where $\mathbf{Q}_0$ represents a reference shape, **X** is a shape space vector (or state vector) and W is a shape matrix. The B-spline template now is represented by a reference B-spline $\mathbf{Q}_0$ and a shape space vector. The N_x x N_Q shape matrix W enforce that the deviations from the reference spline are restricted to geometrically meaningful deformations. As an example, the affine transformation can be represented in shape space via the following transformations:

$$\mathbf{Q} = W\mathbf{X} + \mathbf{Q}_0 \tag{6}$$

$$W = \begin{bmatrix} 1 & 0 & \mathbf{Q}_0^x & 0 & 0 & \mathbf{Q}_0^y \\ 0 & 1 & 0 & \mathbf{Q}_0^y & \mathbf{Q}_0^x & 0 \end{bmatrix} \tag{7}$$

and

$$\mathbf{X} = [d_1 \;\; d_2 \;\; A_{11}-1 \;\; A_{22}-1 \;\; A_{21} \;\; A_{12}] \tag{8}$$

The first two column of the shape matrix W represents the two dimensional (2D) translation and the remaining four columns comprise one rotation and three deformations (horizontal, vertical and diagonal). The dimension of the shape space N_x is usually small compared to the size of the spline vector N_Q.

After defining the shape space, the next part of tracking algorithm is to use curve fitting technique to measure the current position and orientation of the underwater pipeline or cable. In this work the framework introduced by the Blake and Isard is used [7].

If $c_f(s)$ expressed the image feature curve obtained using the one dimensional feature detector and $c_0(s)$ is a pattern curve then, the whole tracking is the estimate $c(s)$, a B-spline curve that is a deformation of $c_0(s)$ and that approximate $c_f(s)$. This approximation can be express as a minimization problem:

$$\min_{\mathrm{X}} \;\; \left\| W\mathbf{X} + \mathbf{Q}_0 - \mathbf{Q}_f \right\|^2 \tag{9}$$

which is the square of the residual norm. Generally, measurements made from images are noisy due to dynamic nature of underwater environments and several other reasons and it is necessary to increase the tolerance for image noise. To overcome the effect of noise a mean contour shape and Tikhonov regularization are used to bias the fitted curve toward the mean shape c_m to the degree determined by regularization constant as shown in Equation 10.

$$r = \arg\min\left(\Omega^2 \left\| c(s) - c_m(s) \right\|^2 + \left\| c(s) - c_f(s) \right\|^2 \right) \tag{10}$$

The expression can be represents conveniently in shape space as:

$$\min_{\mathrm{X}} \;\; \Omega^2 \left\| \mathbf{X} - \mathbf{X}_m \right\|^2 + \left\| \mathbf{Q} - \mathbf{Q}_f \right\|^2 \text{ with } \mathbf{Q} = W\mathbf{X} + \mathbf{Q}_0 \tag{11}$$

to avoid the influence of the position and orientation of the mean contour and from the features of other objects in the background in the regularization term, weight matrix $\overline{S}$ is introduced as shown in Equation 12.

$$\min_{\mathrm{X}} \;\; \left\| \mathbf{X} - \mathbf{X}_\mathrm{m} \right\|^T \overline{S} \left\| \mathbf{X} - \mathbf{X}_\mathrm{m} \right\| + \left\| \mathbf{Q} - \mathbf{Q}_f \right\|^2 \tag{12}$$

where $\overline{S} = \Omega H$ and H is the spare of B-spline function. Since actual image processing is discrete, by using the definition given in [7] the curve fitting problem is expressed in a discrete form as follows:

$$\min_{\mathrm{X}} \;\; \left\| \mathbf{X} - \mathbf{X}_\mathrm{m} \right\|^T \overline{S} \left\| \mathbf{X} - \mathbf{X}_\mathrm{m} \right\| + \sum_{i=1}^{N} \frac{1}{\sigma_i^2} \left(v_i - \mathbf{h}(s_i)^T [\mathbf{X} - \overline{\mathbf{X}}] \right)^2 \tag{13}$$

where v_i and $\mathbf{h}(s_i)^T$ are given in Equation 14 and Equation 15, respectively. Introducing the concept of information matrix S_i and information weight sum $\mathbf{Z}_i$ from the stochastic process, the algorithm for finding the best-fitting curve is summarized as follows:

- Select N regularly equal-spaced sample points $s=s_i$, $i=1,\ldots,N$, with inter-sample space h, along the entire curve $c(s)$ so that, in the case of an open curve $s_1=0$, $s_{i+1}=s_i+h$ and $s_N=L$.
- For each i, find the position of $c_f(s)$ by applying 1D feature detector along the normal line passing though $c(s)$ at $s=s_i$.
- Initialize $\mathbf{Z}_0 = 0, \;\; S_0 = 0$

  Iterate, for $i=1,\ldots,N$

  $$v_i = \left(c_f(s_i) - \overline{c}(s_i) \right) . \overline{\mathbf{n}}(s_i) \tag{14}$$

  $$\mathbf{h}(s_i)^T = \overline{\mathbf{n}}(s_i)^T U(s_i) W \tag{15}$$

  $$S_i = S_{i-1} + \frac{1}{\sigma_i^2} \mathbf{h}(s_i) \mathbf{h}(s_i)^T \tag{16}$$

  $$\mathbf{Z}_i = \mathbf{Z}_{i-1} + \frac{1}{\sigma_i^2} \mathbf{h}(s_i) v_i \tag{17}$$

  where $n(s_i)$ is the normal unit vector of curve $\overline{c}(s)$ at $s=s_i$, and $\sigma_i^2 = N_B$.
- The aggregated observation vector is $\mathbf{Z}=\mathbf{Z}_N$ with the associated statistical information $S=S_N$.
- The best-fitting curve is given in shape-space by:

  $$\hat{\mathbf{X}} = \overline{\mathbf{X}} + (\overline{S} + S)^{-1} \mathbf{Z} \tag{18}$$

The term S_i (information matrix) is a measurement of the weight of each intermediate estimate **X**, $\mathbf{Z}_i$ (information weight sum) accumulates the influence of the mean shape c_m,.

5. Dynamic Tracking

Any tracking system required a model of how the system is expected to evolve or behave over time. In this work, second order auto-regressive process or ARP is used. An autoregressive process is a time series modeling strategy which takes into account the historical data to predict the current state value. The simplest autoregressive model is the linear model where the AUV is assumed to have a constant velocity model with respect to the object. It is best described by the following second order autoregressive model:

$$\mathbf{X}_t - \overline{\mathbf{X}} = A_2(\mathbf{X}_{t-2} - \overline{\mathbf{X}}) + A_1(\mathbf{X}_{t-1} - \overline{\mathbf{X}}) + B_0\mathbf{w}_k \quad (19)$$

where **w** is a random Gaussian noise with zero mean and unit standard deviation, A and B are matrices representing the deterministic and stochastic components respectively, $\overline{\mathbf{X}}$ is the steady state mean and $\mathbf{X}_t$ is the position of object at time t. These parameters are needed to be tuned appropriately for expected motion in order to obtain best tracking results. If β and f are expressed the damping rate and the frequency of oscillation of the harmonic motion respectively then according to the theory of control system they must set to zero for constant velocity model, so that the coefficients of the dynamic model are defined as:

$$A_1 = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{pmatrix}, \; A_2 = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \text{ and } B_0 = \begin{pmatrix} 3 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

where A_1 and A_2 are standard for all second order constant velocity model. The problem is the estimation of B_0 and it required a tuning from the experiment because it defines the standard deviation of the noise. Equation 19 can be simplified by defining:

$$\chi_t = \begin{pmatrix} \mathbf{X}_{t-1} \\ \mathbf{X}_t \end{pmatrix}, \quad (20)$$

and then Equation 19 can be rewritten as:

$$\chi_t - \overline{\chi} = A(\chi_{t-1} - \overline{\chi}) + B\mathbf{w}_k \quad (21)$$

where

$$A = \begin{pmatrix} 0 & I \\ A_2 & A_1 \end{pmatrix}, \overline{\chi} = \begin{pmatrix} \overline{\mathbf{X}} \\ \overline{\mathbf{X}} \end{pmatrix} \text{ and } B = \begin{pmatrix} 0 \\ B_0 \end{pmatrix}$$

The second order state χ_t has a mean and covariance is given below:

$$\hat{\chi}_t = \varepsilon[\chi_t] \text{ and } \vec{P}_t = v[\chi_t]$$

A Kalman filter is design to merge the information from the predicted state and the best fitting curve obtain from Equation 18. A complete one step cycle of tracking is given below:

1. Predict shape space vector χ_t using the dynamic model:

$$\tilde{\chi}_t - \overline{\chi} = A(\hat{\chi}_{t-1} - \overline{\chi}) \quad (22)$$

$$\tilde{\vec{P}}_t = A\tilde{\vec{P}}_{t-1}A^T + BB^T \quad (23)$$

2. Apply Equation 14 to Equation 18 to estimated best fitted state of object.

3. For each measurement the state estimation is update as follows:

$$\mathbf{K}_t = \tilde{\vec{P}}_t\mathbf{H}^T\left(S_t\mathbf{H}\tilde{\vec{P}}_t\mathbf{H}^T + I\right)^{-1} \quad (24)$$

$$\hat{\chi}_t = \tilde{\chi}_t + \mathbf{K}_t\mathbf{Z}_t \quad (25)$$

$$\vec{P}_t = (I - \mathbf{K}_t S_t \mathbf{H})\tilde{\vec{P}}_t \quad (26)$$

and

$$\mathbf{H} = (0 \;\; I) \quad (27)$$

6. Results and Discussion

This section presents the results that obtained by testing the purposed underwater pipeline or cable tracking system for AUV on real image sequences. In general, the accuracy and the performance of the tracking algorithm improve as the number of feature point in the curve fitting stage increase. However, as the number of feature points increases the computational load become heavier. There is an obvious trade-off between accuracy of the tracking algorithm and the computational time. To achieve the balance between performance and efficiency, 20 feature points (10 on each side) were used. Figure 4 shows the graph of measured and the actual position of the underwater pipeline on real underwater image sequences. It is observed that the maximum error is less then 10 pixels which show the robustness of tracking algorithm.

To solve the initial value problem of the Kalman filer it has been assumed that, when tracking was started pipeline was near the center of the image.

7. Conclusion

In this paper a robust vision based system for underwater pipeline tracking has been presented. The developed system successfully detects the pipeline and track in real image sequences. The algorithm has been implemented in Matlab environment and all tests have been conducted on a 1.70GHz Pentium IV machine executing windows XP.

The B-spline contour deforms successfully, based on the feature detected and the orientation and position of the pipeline has been computed. To conform the validity of the purposed system many experiments conducted on real and synthetic underwater pipeline images. The maximum error that has been achieved is less then 10 pixels.

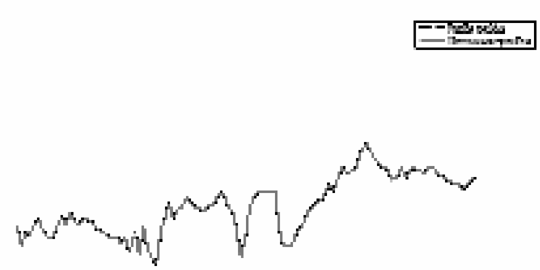


Figure 4 - Comparison of Actual and the Measured Position of the UnderwaterPpipeline

A lot more work need to be done to refine this approach. Further studies on improving the algorithm structure and calculation steps to achieve better computation time need to be investigated. In order to improve tracking and to make the algorithm more robust new method for feature extraction and image enhancement will be explored.

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